

Frontdoor Programming Assignment

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Reading in data, importing packages and setting seed. Creating new features for diamond volume and the log price of the diamond. The 4 most important characteristics for determining the cost of a diamond are caret, cut, color and clarity. The data does not include the number of carets per diamond. To work around this, we use the x, y, and z features to create the volume of each diamond as feature. The volume of a diamond directly affects its weight, and the weight of a diamond plays a large factor in its price. In this way a missing feature can be substituted.

The log price is a a normalization feature since the price of a diamond can vary greatly. Predictions will be made with both prices in order to establish a better idea of correlation.

```
knitr::opts_chunk$set(echo = TRUE)
set.seed(0351)
library(caret)
```

```
## Warning: package 'caret' was built under R version 3.6.1
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

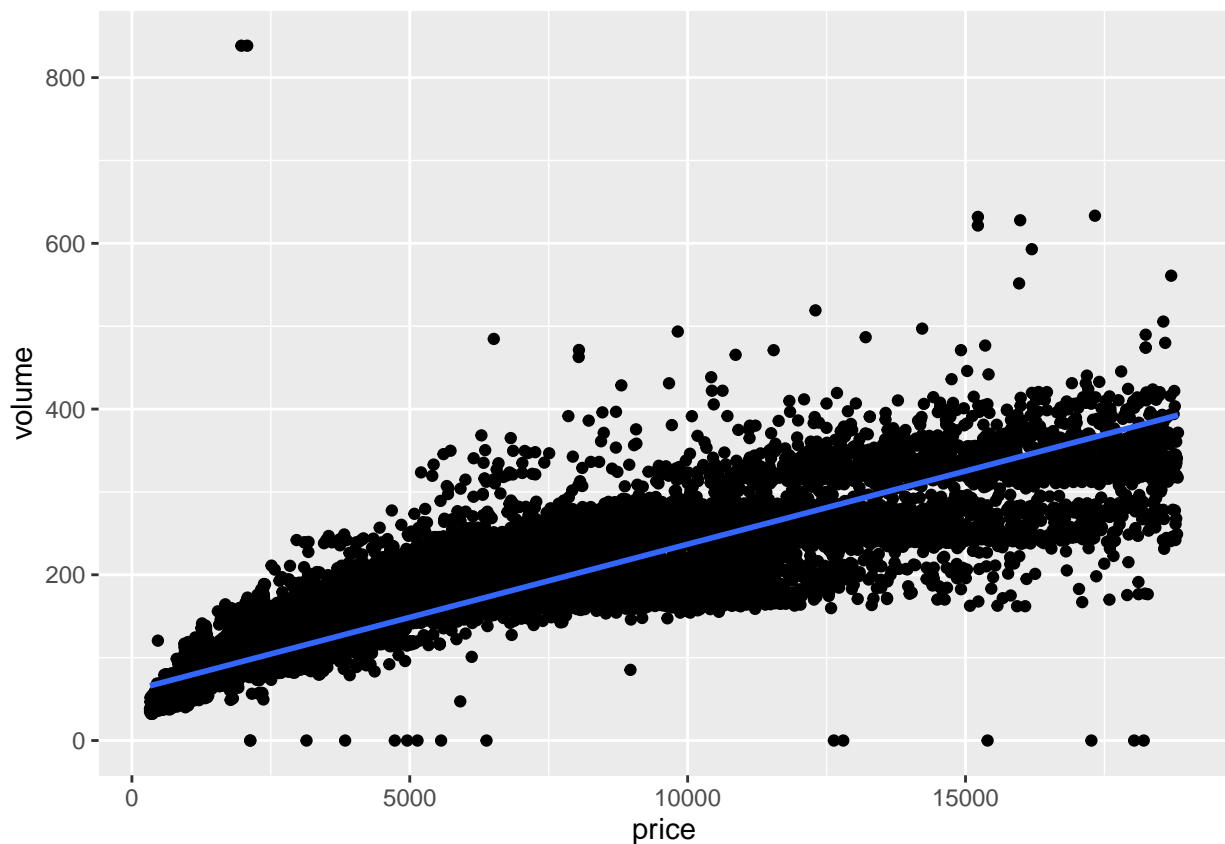
```
## Warning: package 'ggplot2' was built under R version 3.6.1
```

```
library(ggplot2)
diamonds <- read.csv("C:/Users/nickm/MlinR/DiamondsPredictions/Diamonds.csv")
diamonds <- as.data.frame(diamonds)
diamonds$volume <- diamonds$x * diamonds$y * diamonds$z
diamonds$log price <- log10(diamonds$price)
```

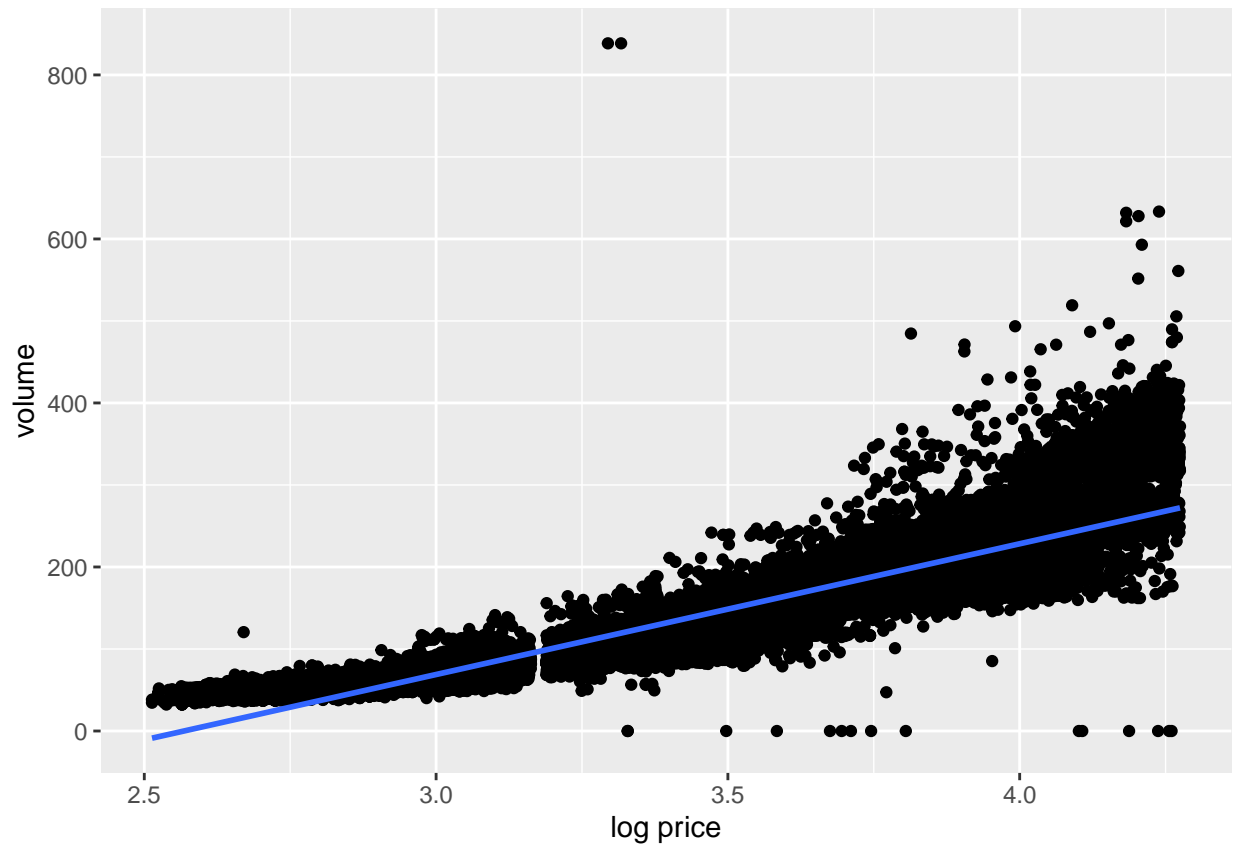
Exploratory data visualization. Plotting the color, cut and clarity against the price did not yield any linearity, suggesting the diamond pricing within categories is relatively fixed. Plotting the price against the volume of the diamond, however, suggests a more correlational relationship than any of the other features.

Plotting the log price against the diamond's volume reinforces this idea, as normalizing the price makes clear an even more linear relationship.

```
ggplot(diamonds, aes(price, volume)) +  
  geom_point() +  
  geom_smooth(method = "lm", se = FALSE)
```



```
ggplot(diamonds, aes(`log price`, volume)) +  
  geom_point() +  
  geom_smooth(method = "lm", se = FALSE)
```



Splitting the data into 80% training and 20% testing data. Removing features that do not explain a significant amount of variance in the data or that were used to calculate volume.

```
data_sample <- floor(0.8 * nrow(diamonds))
index <- sample(seq_len(nrow(diamonds)), size = data_sample)
diamonds_train <- diamonds[index,]
diamonds_test <- diamonds[-index,]

diamonds_train <- diamonds_train[, c(-5, -6, -7, -8, -9)]
diamonds_test <- diamonds_test[, c(-5, -6, -7, -8, -9)]
```

Setting a linear model to measure the effects of the features on the price of the diamond. The summary for the log price suggests that cut does not play a large role in the diamond's price; the difference in variance confirms this. The log model is then updated to remove the cut feature.

```
diamonds_lm <- lm(price ~ cut + color + clarity + volume,
                  data = diamonds_train)
summary(diamonds_lm)
```

```
##
## Call:
## lm(formula = price ~ cut + color + clarity + volume, data = diamonds_train)
##
## Residuals:
```

	Min	1Q	Median	3Q	Max
	-41458	-681	-199	440	22758

```
##
## Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-6906.1544	71.2940	-96.87	<2e-16 ***
cutGood	472.9736	46.2244	10.23	<2e-16 ***
cutIdeal	662.1874	42.0521	15.75	<2e-16 ***
cutPremium	612.7962	42.4024	14.45	<2e-16 ***
cutVery Good	593.8625	42.9180	13.84	<2e-16 ***
colorE	-244.4200	25.4608	-9.60	<2e-16 ***
colorF	-296.9286	25.7149	-11.55	<2e-16 ***
colorG	-472.8490	25.1856	-18.77	<2e-16 ***
colorH	-908.2424	26.7270	-33.98	<2e-16 ***
colorI	-1410.8053	30.0786	-46.90	<2e-16 ***
colorJ	-2258.8599	36.8883	-61.23	<2e-16 ***
clarityIF	5214.4944	72.4008	72.02	<2e-16 ***
claritySI1	3409.8377	62.1965	54.82	<2e-16 ***
claritySI2	2477.2105	62.4531	39.66	<2e-16 ***
clarityVS1	4342.2463	63.4504	68.44	<2e-16 ***
clarityVS2	4053.8432	62.4911	64.87	<2e-16 ***
clarityVVS1	4847.1150	67.1138	72.22	<2e-16 ***
clarityVVS2	4745.0318	65.3042	72.66	<2e-16 ***
volume	54.4333	0.1028	529.25	<2e-16 ***

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1231 on 31981 degrees of freedom
## Multiple R-squared:  0.9042, Adjusted R-squared:  0.9041
## F-statistic: 1.677e+04 on 18 and 31981 DF,  p-value: < 2.2e-16
```

```
diamonds_log_lm <- lm(`log price` ~ cut + color + clarity + volume,
                      data = diamonds_train)
summary(diamonds_log_lm)
```

```
##
## Call:
## lm(formula = `log price` ~ cut + color + clarity + volume, data = diamonds_train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.3354 -0.0946  0.0243  0.1066  1.7765
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.374e+00  8.770e-03 270.745 < 2e-16 ***
## cutGood      4.270e-03  5.686e-03   0.751   0.453
## cutIdeal     4.694e-03  5.173e-03   0.907   0.364
## cutPremium   9.842e-04  5.216e-03   0.189   0.850
## cutVery Good -2.146e-05  5.279e-03  -0.004   0.997
## colorE       -2.492e-02  3.132e-03  -7.958 1.81e-15 ***
## colorF       -1.971e-02  3.163e-03  -6.232 4.66e-10 ***
## colorG       -5.603e-02  3.098e-03 -18.086 < 2e-16 ***
## colorH       -1.096e-01  3.288e-03 -33.328 < 2e-16 ***
## colorI       -1.762e-01  3.700e-03 -47.620 < 2e-16 ***
## colorJ       -2.454e-01  4.538e-03 -54.077 < 2e-16 ***
## clarityIF     4.161e-01  8.906e-03  46.723 < 2e-16 ***
## claritySI1    2.889e-01  7.651e-03  37.756 < 2e-16 ***
## claritySI2    2.138e-01  7.682e-03  27.826 < 2e-16 ***
## clarityVS1    3.523e-01  7.805e-03  45.131 < 2e-16 ***
## clarityVS2    3.321e-01  7.687e-03  43.207 < 2e-16 ***
## clarityVVS1   3.797e-01  8.256e-03  45.989 < 2e-16 ***
## clarityVVS2   3.744e-01  8.033e-03  46.605 < 2e-16 ***
## volume       5.877e-03  1.265e-05 464.546 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1514 on 31981 degrees of freedom
## Multiple R-squared:  0.8819, Adjusted R-squared:  0.8818
## F-statistic: 1.326e+04 on 18 and 31981 DF, p-value: < 2.2e-16

diamonds_log_lm <- lm(`log price` ~ color + clarity + volume,
                      data = diamonds_train)
```

Predictions for the testing set are made here. The linear model model for price trained on the training data is set to the test data and used to predict price points for the testing diamonds. The absolute value of those points (the diamond price can't be negative) is then fed into a correlation matrix. The same is done for predictions based on the log price for the diamonds.

The correlation matrix for each linear model presents a clear view that the predicted values for both the price and log price are very accurate! Most of the diamond price points correlate very strongly with the the fit, upper and lower bounds - all the correlation values are at least 0.95.

Interestingly, the log price linear model showed even more correlation than the price model, despite having one less feature. The logging of the prices must have reduced variance for more accurate predictions.

```
lm_predictions <- predict(diamonds_lm, newdata = diamonds_test,
                          interval = "prediction", level = 0.95)
test_preds <- data.frame(cbind(actuals=diamonds_test$price,
                              predicted=lm_predictions))
test_preds$fit <- abs(test_preds$fit)

correlation_accuracy <- cor(test_preds)
correlation_accuracy
```

```
##          actuals          fit          lwr          upr
## actuals 1.0000000 0.9638806 0.9580998 0.9581044
## fit     0.9638806 1.0000000 0.9910385 0.9910459
## lwr     0.9580998 0.9910385 1.0000000 1.0000000
## upr     0.9581044 0.9910459 1.0000000 1.0000000
```

```
lm_log_predictions <- predict(diamonds_log_lm, newdata = diamonds_test,
                              interval = "prediction", level = 0.95)
test_log_preds <- data.frame(cbind(actuals=diamonds_test$price,
                                   predicted=lm_log_predictions))
test_log_preds$fit <- abs(test_log_preds$fit)

correlation_log_accuracy <- cor(test_log_preds)
correlation_log_accuracy
```

##		actuals	fit	lwr	upr
##	actuals	1.0000000	0.9547039	0.9547019	0.9547059
##	fit	0.9547039	1.0000000	1.0000000	1.0000000
##	lwr	0.9547019	1.0000000	1.0000000	1.0000000
##	upr	0.9547059	1.0000000	1.0000000	1.0000000